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1 Introduction

The fact that the Global Financial Crisis, and the Great Recession it ushered in, was largely unforeseen, has led to the common opinion that macroeconomic models and analysis is deficient in some way. Of course it has probably always been true that businessmen, journalists and politicians have agreed on the proposition that economists can't forecast recessions. Yet we see an enormous published literature that presents results which suggest it is possible to do so, either with some new model or some new estimation method e.g. Kaufman (2010), Galvao (2006), Dueker (2005), Wright (2006) and Moneta (2005). Moreover, there seem to be no shortage of papers still emerging that make claims along these lines. So a question that naturally arises is how one is to reconcile the existence of an expanding literature on predicting recessions with the scepticism noted above?

Many reasons have been given for why one might not be able to predict recessions. One is that the economy is complex. However, many systems such as weather are also complex, and yet the record of meteorologists seems quite good. Another is that there are too few recessions, so one is faced with a small number of events. Now there are more bear equity markets than recessions, yet the extra observations available on these does not seem to have produced a more successful prediction record of stock market crashes. Clearly, the answer must lie elsewhere.

In this paper we argue that the problems in predicting recessions stem from the nature of the definition of a recession. Much of the literature that claims success does not predict recessions as such. Rather it focusses upon either whether one can predict growth in economic activity or whether one can identify the *current status* on the economy - what is now often referred to as "nowcasting" - rather than forecasting. Still other papers focus on the ability to predict what we will call a "recession-derived event". Success in this however often has few implications for the ability to predict a recession. Thus our paper seeks to provide a review of the literature on predicting recessions. The review leads to the contention that it is extremely difficult to predict recessions. Understanding why this is so leads to an appreciation of the barriers to be faced in the task and also suggests that many of the claims made about how the forecasting record can be improved should be treated with scepticism. This is not to deny that some of these suggestions might be able to *improve our understanding* of business cycle issues, even if they do not improve the forecasting capacity. Moreover, being aware of the limits to forecasting suggests that we should focus our research on questions that we might have a better chance of addressing e.g. whether it is possible to predict how long a recession will last once it is initiated.

In the next section we give a definition of a recession that revolves around isolating peaks and troughs in a series that represents economic activity. Although our presentation will concentrate upon quarterly data it can be extended to monthly series, although there is little to be gained for an understanding of the prediction issues from doing so. Section 3 then uses that definition to explain why it is unlikely that recessions can be predicted in either the Euro area or the US utilizing most currently available data sets. Any improvement will have to come from access to information that captures the future shocks that are likely to affect the economy and the origin of these does not seem to be in the past. At this stage we slightly modify our focus away from predicting recessions *per se* and ask what is the probability of predicting negative growth in economic activity one period ahead? Because a recession gets initiated with a period of negative growth, if such an event cannot be predicted it will be hard to predict a recession, as the latter involves studying a sequence of signs of future growth rates. We often find it useful to concentrate on this simpler event as it avoids difficulties in defining exactly what a recession is.

Section 4 then asks whether the problem lies in the perspective that was taken in section 3. In order to simplify the argument section 3 took growth in economic activity as being determined linearly by the state of the economy and past growth rates. It might be that the relation is a non-linear one and thus we might want to allow for various types of non-linearity. As an illustration Markov Switching models were fitted to Euro-area and U.S. growth. Using this model to produce forecasts it is found that there is even less ability to predict future negative growth, unless a negative growth rate has already been observed.

Section 5 investigates what other information might be useful in predicting future growth rates. Here there is a growing literature on that question, some of which claims success for variables such as the yield spread and various leading indicators. Some of the European and US literature also uses a range of variables coming from micro-economic surveys, incorporating them into multivariate models that might be utilized to predict future events. One that has received some attention is the Qual-VAR model of Dueker (2005). We discuss some econometric problems with this paper, and its use in forecasting the 2001 recession, which makes us feel that the claims for its effectiveness are perhaps exaggerated.

Finally, section 6 looks at papers working with a "recession-derivative indicator" (RDI) e.g. Wright (2006), rather than a recession. Papers in this literature claim to have an impressive record of predicting recessions, whereas they are actually predicting the RDI. We show that there are two effects of switching to an RDI perspective. Firstly, the unconditional probability of encountering an RDI event is much higher than that of a recession - often twice as high- and what may look like predictive success is simply an artifact of the definition. Secondly, the timing of the origin of an RDI event is very different to that of a recession. Mostly the event happens before a recession and so it may look as if one has managed to predict recessions in advance, particularly if only graphical evidence is tendered. Again, this is an artifact of the definition.

2 Recognizing a Recession

Because our discussion will involve quarterly data economic activity Y_t is mostly measured by GDP. If monthly data had been the focus one would need to have used a number of indicators. It should be conceded that, even in the quarterly case, one sees a use of quantities such as the unemployment rate, industrial production and retail trade to measure economic activity. Regardless of whether a single variable or a variety of series are utilized to construct a measure of Y_t the task is to determine where the turning points in Y_t occur. These turning points are peaks and troughs in economic activity and they enable one to mark off periods of time spent in expansions and contractions. It is worth noting that we will always study turning points in $y_t = \ln Y_t$. The turning points are the same in both series due to log being a monotonic transformation, but it is more convenient to work with y_t, as the changes in y_t are approximately growth rates.

A program that we use to find the turning points is the BBQ program, which derives from the philosophy set out in Bry and Boschan (1983) and underlies much of the NBER business cycle dating philosophy. BBQ is a WYSIWYG program and the rules used to locate a set of turning points are as follows.

1. A *peak* occurs at time t if y_t is greater than $\{y_{t-1}, y_{t-2}, y_{t+1}, y_{t+2}\}$. Thus a peak occurred in Euro area GDP in 1980:1 as seen in the following observations on the log of Euro GDP for $\{\ y_{1979:3}, y_{1979:4}, y_{1980:1}, y_{1980:2}, y_{1980:3}, y_{1980:4}, y_{1981:1}\}$:

{13.8100,13.8194, *13.8288*, 13.8241, *13.8235*, 13.8240, 13.8250}. A trough is defined symmetrically and it is clearly identified as being at 1980:3, making the recession of the early 1980s two quarters long. Why choose two quarters on either side of the potential peak? The reason is the feeling that a recession (time between peak and a trough) should last for some minimal time, otherwise recessions will be called too often. By convention this has become 2 quarters (or five months if one uses monthly data)[1]. This could be changed if one wished. For the Euro area it would matter a great deal if one moved to one quarter as the minimum length of a recession, since over 1970-2009 there were seven quarters in which there was negative growth in GDP but BBQ does not identify a recession. This is also true for other countries such as Australia and the US (in fact Australia only had one period of negative growth during the Great Recession). The point is that a recession is an extreme event and so some convention needs to be established about how we recognize that the behavior of GDP is extreme enough. One might also apply some quantitative rules e.g. the decline in GDP has to be larger than some specified value. This might be used to eliminate some weak recessions identified by BBQ and this is often done informally by business cycle dating committees. It should be noted that the BBQ rule does not coincide with that often used in the press that a recession is two consecutive periods of negative growth, nor rules that sometimes appear in the academic literature e.g. Fair (1993), which have a recession occurring in time t if there are two consecutive negative growth rates in GDP in the five quarters that begin in t. We return to these alternative definitions in section 6.

2. There are other constraints that BBQ uses such as a minimal length for a complete cycle i.e. the period from a peak to peak, but these are of smaller importance and won't detain us here.

3. Once the turning points have been isolated it is possible to determine when the economy was in either a recession or an expansion. It is convenient to summarize this information by designating a series S_t that takes the value 1 when we are in an expansion and zero when we are in recession. Thus, when we are concerned with predicting a recession at time t, we will be asking what the chance is that $S_{t+1} = 0$? It is here that one might often prefer to work with a series on S_t constructed by some business cycle dating committee, given that such a group might be able to utilize auxiliary information that

[1] The NBER Dating Committee uses the five monthly rule when finding the turning points in the US economy.

an automated program such as BBQ does not allow for. Thus BBQ identifies a trough in 1993:1 but the weak growth in 1993:2 of .07% clearly led the Euro Area Dating Committee to prefer a later date for the trough.[2] For the US, BBQ does not recognize a recession in 2001 since each negative growth rate in GDP was followed by a positive one of larger magnitude.[3] But the NBER Dating Committee do identify a recession in 2001. Apart from these exceptions, the correspondence between the turning points identified by BBQ based on GDP and these "official" dates is good. For empirical work on Europe we will use the BBQ dates, but we will generally adopt the NBER ones for the US, since some of the RDIs we want to investigate later focus on the NBER-defined recessions and expansions.

4. The condition for a peak can be expressed in terms of growth rates. When that is done a peak at t occurs when $\{\Delta y_t > 0, \Delta_2 y_t > 0, \Delta y_{t+1} < 0, \Delta_2 y_{t+2} < 0\}$, where $\Delta_2 y_t = y_t - y_{t-2} = \Delta y_t + \Delta y_{t-1}$ is six-monthly growth. Another way of expressing this is to adopt the conventional definition that a recession starts the period after a peak while an expansion begins the period after a trough - see Estrella and Trubin (2006). Using that perspective we can alternatively express a turning point as a change in state viz. $S_t = 1 \rightarrow S_{t+1} = 0$ if there is a peak at t. Thus, if $\{\Delta y_t > 0, \Delta_2 y_t > 0, \Delta y_{t+1} < 0, \Delta_2 y_{t+2} < 0\}$, then we have a change from expansion to recession. If these conditions are not satisfied then we remain in the current state i.e. $S_t = 1 \rightarrow S_{t+1} = 1$. Thus to know if there has been a change in state we will need to know *future information* in the form of $\{\Delta y_{t+1} < 0, \Delta_2 y_{t+2} < 0\}$. Moreover, the corollary is that if you know S_t you must have used future information to determine it (the dating committees of course set the turning points quite a time after they happened).

To look at this more formally we observe that the S_t generated by BBQ can be written in the recursive form

$$\begin{aligned} S_{t+1} &= S_t S_{t-1} \left[1 - \mathbf{1}\left(\Delta y_{t+1} \leq 0\right) \mathbf{1}\left(\Delta y_{t+1} + \Delta y_{t+2} \leq 0\right)\right] \\ &\quad + S_t \left(1 - S_{t-1}\right) \\ &\quad + \left(1 - S_t\right)\left(1 - S_{t-1}\right) \mathbf{1}\left(\Delta y_{t+1} > 0\right) \mathbf{1}\left(\Delta y_{t+1} + \Delta y_{t+2} > 0\right), \end{aligned} \tag{1}$$

[2] In fact they set it at 1993:3. This has to be debateable given that growth in that quarter was .4%, almost stronger than what happened in 1993:4.

[3] In the early releases of GDP in 2003 there were three periods of successive negative growth and so BBQ did then identify a 2001 recession.

where $\mathbf{1}(\mathcal{A}) = 1$ if $\mathcal{A}$ is true and zero otherwise.[4] We wish to predict S_{t+1}. More generally, (1) points to the fact that to predict S_{t+1} we need to have some idea of S_t, S_{t-1} and the future signs of Δy_{t+1} and $\{\Delta y_{t+1} + \Delta y_{t+2}\}$. Thus we need to indicate what information is available when predicting S_{t+1}, and also how one is to predict S_t, S_{t-1}, and the signs of Δy_{t+1},$\{\Delta y_{t+1} + \Delta y_{t+2}\}$ with that information.

It is worth looking at (1) when we are interested in predicting a recession given that, at time t, we are in an expansion i.e. $S_t = 1, S_{t-1} = 1$. Then it becomes

$$S_{t+1} = [1 - \mathbf{1}(\Delta y_{t+1} \leq 0)\, \mathbf{1}(\Delta y_{t+1} + \Delta y_{t+2} \leq 0)]$$

and

$$\begin{aligned} \Pr(S_{t+1} &= 1|F_t) = [1 - E\{\mathbf{1}(\Delta y_{t+1} \leq 0)\, \mathbf{1}(\Delta y_{t+1} + \Delta y_{t+2} \leq 0)\,|F_t\}] \\ &\geq [1 - E\{\mathbf{1}(\Delta y_{t+1} \leq 0)\,|F_t\}] \end{aligned}$$

where F_t is the information available at t (including $S_{t-1} = 1, S_t = 1$). Consequently,

$$\Pr(S_{t+1} = 0) = 1 - \Pr(S_{t+1} = 1) \leq E\{\mathbf{1}(\Delta y_{t+1} \leq 0|F_t) = \Pr(\Delta y_{t+1} \leq 0|F_t).$$

So an upper bound to the probability of a recession at $t = 1$ is found by looking at $\Pr(\Delta y_{t+1} \leq 0|F_t)$. For expository purposes it is often simplest to study whether we can predict the event $\mathbf{1}(\Delta y_{t+1} \leq 0)$, rather than the joint event $\mathbf{1}(\Delta y_{t+1} \leq 0)\, \mathbf{1}(\Delta y_{t+1} + \Delta y_{t+2} \leq 0)$, and we will often do this in what follows. But it should be borne in mind that the joint event will be harder to predict than the single period of negative growth.

3 Predicting a Recession with State and GDP Growth Data

We are then ultimately interested in whether a recession can be predicted at time $t+1$ when we are at t i.e. in predicting whether $S_{t+1} = 0$. This depends

[4] There is a small complication caused by completed cycles having a minimum duration of five quarters. Only occasionally does this constraint bite. It should be observed that this relationship shows that one does not need a Markov Switching model to predict business cycle states. It is the definition of a recession which provides the structure needed to do the prediction.

upon growth rates in economic activity at $t+1$ and $t+2$. It is necessary to specify what information would have been available at time t that would be useful to predict the value of S_{t+1} (or the growth rates).[5] If the growth rates in activity were independent then knowing these past values will be of no use in predicting the future growth rates *per se*. Now in many countries there is very little persistence in growth rates of GDP e.g. the UK and Australia. But in the US and the Euro area there is moderately strong first order serial correlation in growth rates. *Prima facie* this might look advantageous but we will see later that it is not.

It is worth getting some idea of the determinants of the probability of a defined event given a determinant. Denote R_t as a binary indicator of the event, with $R_t = 1$ if it occurs and zero otherwise. Thus R_t could be a recession or it might just be a period of negative growth. For convenience however we will refer to it as a recession.

Consider the regression of R_t on 1 and x_t. Hence the linear relation will be

$$R_t - \bar{R} = (x_t - \bar{x})\beta,$$

where $\bar{R}$ and $\bar{x}$ are the sample means of R_t and x_t. Then

$$\begin{aligned}
\hat{\beta} &= \frac{\frac{1}{T}\sum_{t=1}^{T}(x_t - \bar{x})(R_t - \bar{R})}{\frac{1}{T}\sum_{t=1}^{T}(x_t - \bar{x})^2} \\
&= \frac{\frac{1}{T}\sum_{t=1}^{T}(x_t - \bar{x})R_t}{var(x_t)} \\
&= \frac{\frac{T_r}{T}(\bar{x}_R - \bar{x})}{var(x_t)}
\end{aligned}$$

where $T_R = \#$ of periods in recession and $\bar{x}_R$ is the average of x_t over periods spent in recession. Hence the prediction of $R_t - \bar{R}$ is

$$\begin{aligned}
\hat{R}_t - \bar{R} &= (x_t - \bar{x})\frac{\frac{T_r}{T}(\bar{x}_R - \bar{x})}{var(x_t)} \\
&\Longrightarrow \hat{R}_t = \bar{R} + (x_t - \bar{x})\frac{\frac{T_r}{T}(\bar{x}_R - \bar{x})}{var(x_t)} \\
&= \bar{R}(1 + (x_t - \bar{x})\frac{\frac{T_r}{T}(\bar{x}_R - \bar{x})}{var(x_t)})
\end{aligned}$$

[5] Although we will write Δy_t, S_{t-1} etc. as the available information we will mean all past values of these quantities.

Hence the probability of a recession rises above its unconditional value when x_t is below its sample mean and $\bar{x}_R < \bar{x}$. Now $\frac{(\bar{x}_R - \bar{x})}{var(x_t)} = t_{\bar{x}}/sd(x_t)$, where $t_{\bar{x}}$ is the t ratio that $\bar{x}_R = \bar{x}$ (provided x_t is $i.d.$). Clearly the magnitude of the probability depends upon the magnitude of the t test, the variability in x_t and the fraction of the sample that is recessions. It is possible to generalize the above to handle more than one determinant but for a conceptual understanding it suffices to deal with only one.

Suppose we knew that $S_t = 1$ and $S_{t-1} = 1$ i.e. we were in an expansion at the time the prediction is to be made. Then

$$\begin{aligned}\Pr(S_{t+1} &= 0|F_t) = E\{\mathbf{1}\left(\Delta y_{t+1} \leq 0\right)\mathbf{1}\left(\Delta y_{t+1} + \Delta y_{t+2} \leq 0\right)|F_t\} \\ &= g(F_t)\end{aligned}$$

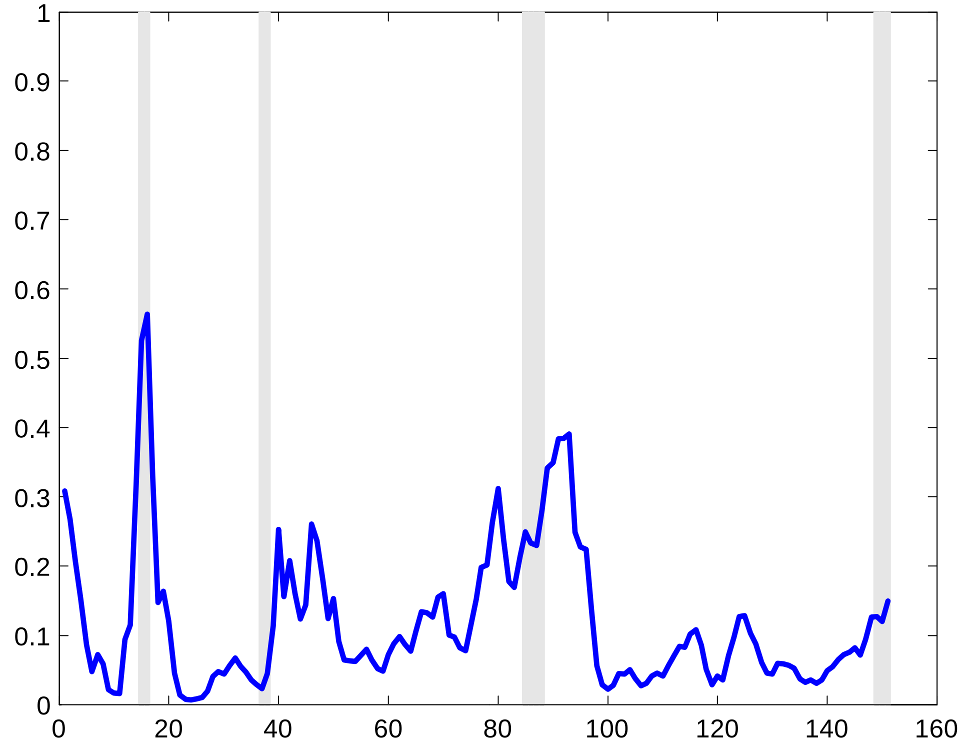
The functional relation $g(\cdot)$ will generally be non-linear for two reasons. One is that the conditional expectations will be non-linear in F_t as they must lie between zero and unity, but it may also be that Δy_{t+j} $(j = 1, 2)$ depends in a non-linear way upon F_t. In most instances $g(\cdot)$ will not be analytically derivable. If the number of elements in F_t is limited then one can use non-parametric methods to estimate $g(\cdot)$ as in Harding and Pagan (2011). Because we are estimating a probability it might be desirable to make the $g(\cdot)$ function monotonic and Harding (2010) shows how one can adjust the non-parametric estimates to impose monotonicity in a reasonably simple way. Sometimes, for example if the mapping between Δy_{t+1} and Δy_{t+2} and F_t is linear, then one can evaluate $E\{\mathbf{1}\left(\Delta y_{t+1} \leq 0\right)\mathbf{1}\left(\Delta y_{t+1} + \Delta y_{t+2} \leq 0\right)|F_t\}$ by simulation methods. An example would be if Δy_t followed an $AR(1)$ process of the form

$$\Delta y_{t+1} = \mu + \rho\Delta y_t + \sigma\varepsilon_t, \qquad \varepsilon_t\tilde{}\,iid\,N\left(0,1\right). \tag{2}$$

and $F_t = \Delta y_t$.

As foreshadowed earlier we will focus upon the ability to predict a negative growth rate i.e. $\Pr(\Delta y_{t+1} < 0|F_t)$. This equals $E\{1(\Delta y_{t+1} < 0)|\Delta y_t)$. In the literature it is often that case that $E(1(\Delta y_{t+1} < 0)|\Delta y_t)$ is assumed to be $\Phi(\Delta y_t)$, where $\Phi(\cdot)$ is the c.d.f for the standard normal. In Harding and Pagan (2011) we argue that there is a strong case for a non-parametric fit, but here we will use the Probit form for simplicity, since the non-parametric estimate of $E(1(\Delta y_{t+1} < 0)|\Delta y_{t-1})$ was much the same as that from a Probit model. With other conditioning variables this might not be true. Figure 1 then looks at the ability to predict $1(\Delta y_{t+1} < 0)$ when information Δy_t

Fig 1 Prob Negative Growth and Recession Periods for Euro Area



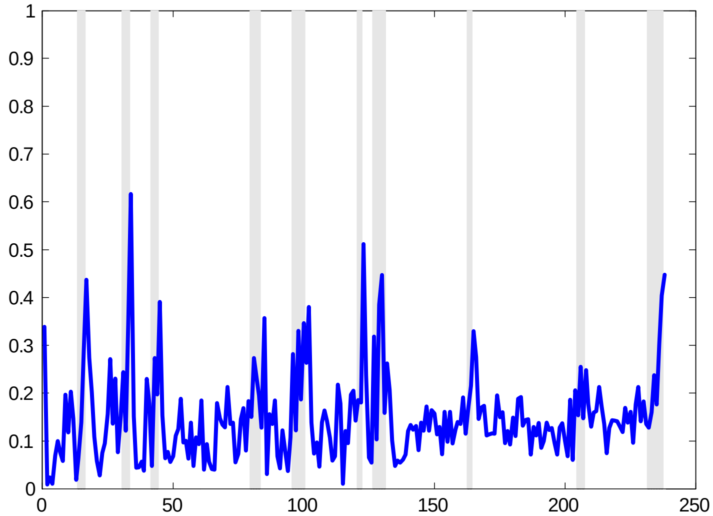
is available for the Euro Area. The grey shaded areas are Euro-Area recessions. Table 1 then gives the probabilities as one moves through the 1992/3 recession.

Table 1 : Probabilities of Predicting $E(\Delta y_{t+1} < 0 \vert \Delta y_t)$			
Euro Area 1992/3 Recession			
Prediction At t/For $t+1$	prob		$1(\Delta y_{t+1} < 0)$
1992:1/1992:2	.03		1
1992:2/1992:3	.38		1
1992:3/1992:4	.26		1
1992:4/1993:1	.24		1

.

This is a typical pattern - the first period of the recession is predicted

Fig 2 Lag Gwth: Prob Neg Growth and Recessions for US



with very low probability but then rises as the recession gets underway. Thus, at the time the recession emerges i.e. $S_{t+1} = 0$, we would have prediction probabilities ($\Pr(\Delta y_{t+1}|\Delta y_t)$) in the various Euro recessions of .09 (1974:4), .06 (1980:2), .03 (1992:2), and .08 (2008:2). If we think that a critical value here is .5 (a fairly common choice) then none of the five recessions would have been predicted using the the most favorable information, in the sense that it is highly unlikely that Δy_t would be available one period before the recession begins.[6] To put these numbers into context, since 11.6% of the time was spent in recession, if you just allocated a value of .116 every period you would be doing better than trying to exploit the information available in growth rates[7]. A similar result holds for the US, with the probabilities varying between .06 and .27 for the recessions since 1953. It should be noted that the unconditional probability of a recession over the period 1953/2 to 2009/3 is .16.

Now an examination of $\Pr(\Delta y_{t+1} \leq 0|\Delta y_t)$ is needed. The fact that there is positive serial correlation (.35) in GDP growth in the Euro area militates against successfully predicting $\Delta y_{t+1} < 0$, since a positive growth

[6]The issue of deciding on a threshold is a difficult one and something we will deal with in a later version of this paper. The choice raises similar issues to balancing Type 1 and Type 2 errors in hypothesis testing.

[7]Using $\Delta y_{t-1}, \Delta y_{t-2}$ and Δy_{t-3} as regressors does not change this conclusion.

in the previous period points towards it being positive again. Indeed, the correlation of $\psi_t = 1(\Delta y_{t+1} < 0)$ with ψ_{t-1} is .33.[8] Hence it is very difficult to predict negative growth coming out of an expansion, and it is only after the recession has arrived that the strong dependence will make the probability of Δy_{t+1} <0 substantial. Using the Euro area data we can compute a non-parametric estimate of the $\Pr(\Delta y_{t+1} < 0|\Delta y_t)$ and, for a small value of Δy_t close to zero, the probability is .16 - so only a little bigger than the unconditional probability[9].

Now, as mentioned above, the choice of Δy_t as information available to forecast the event $\Delta y_{t+1} < 0$ is problematic. It is unlikely that one would know Δy_t when the forecast had to be made. In practice we rarely know what the growth rate in the current quarter is e.g. in Australia the best we would get would be GDP growth for $t-1$ in quarter t. Even then this quantity can be subject to substantial revision and even a possible sign change. In terms of forecasting recessions this has two consequences. One is that it will no longer be the case that S_t can be known. If it was the case that S_{t-1} was known to be unity, then a positive Δy_t would mean that $S_t = 1$, since the peak in y_t would not be at $t-1$. But if we don't know Δy_t then it might be negative. Since a negative growth can occur in an expansion, whether S_t is either 0 or 1 will not be known, and so we will need to predict this as well as $\Delta y_{t+j} (j = 1, 2)$.

To see the effect of being restricted to only knowing Δy_{t-1}, it is useful to look at $E\{1(\Delta y_{t+1}|\Delta y_t)\}$ and $E\{1(\Delta y_{t+1}|\Delta y_{t-1})\}$ *one quarter into a recession.* The probabilities from the European data are then {.62,.11},{.31,.11},{.38,.10}, and {.25,.11} respectively**.** The poor prediction record of the second set of information i.e. Δy_{t-1} comes from the fact that, even after the recession has started, it is not yet known whether there has been a negative growth rate. Thus that piece of extra information would have a significant impact on the ability to predict negative growth. Of course when it comes to predicting recessions the situation is even more complex, as it becomes necessary to predict S_t as this would not be known. Thus we might think that, at best, the information available for predicting S_{t+1} would be S_t and Δy_t and, at

[8]Under a normality assumption for Δy_t Kedem(1980) gave an expression for the serial correlation coefficients of $1(\Delta y_{t+1} > 0)$ in terms of the serial correlation coefficients of Δy_t.

[9]The probability is identical to $E(1(\Delta y_{t+1} < 0)|\Delta y_t)$ given the binary nature of the event $1(\Delta y_{t+1} < 0)$, so we can estimate the probability with a non-parametric estimate of the conditional mean of $1(\Delta y_{t+1} < 0)$.

worst, it would be $S_{t-2}, \Delta y_{t-1}$. This problem of trying to come up with the latest GDP growth outcome is often referred to as "now-casting", and one can see that it is important to get a good estimate.

If S_t is not known we need to make an estimate of it in order to predict recessions. To see how this is done lag (1) by one period to get

$$\begin{aligned} S_t &= S_{t-1}S_{t-2}\left[1-\mathbf{1}\left(\Delta y_t \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+1} \leq 0\right)\right] && (3)\\ &+S_{t-1}\left(1-S_{t-2}\right) && (4)\\ &+\left(1-S_{t-1}\right)\left(1-S_{t-2}\right)\mathbf{1}\left(\Delta y_t > 0\right)\mathbf{1}\left(\Delta_2 y_{t+1} > 0\right) \end{aligned}$$

Substituting (3) into (1), after some rearrangement we would obtain

$$\begin{aligned} S_{t+1} &= S_{t-1}S_{t-2}\left[1-\mathbf{1}\left(\Delta y_{t+1} \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+2} \leq 0\right)\right]\left[1-\mathbf{1}\left(\Delta y_t \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+1} \leq 0\right)\right]\\ &+S_{t-1}\left(1-S_{t-2}\right)\left[1-\mathbf{1}\left(\Delta y_{t+1} \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+2} < 0\right)\right]\\ &+\left(1-S_{t-1}\right)\left(1-S_{t-2}\right)\mathbf{1}\left(\Delta y_t > 0\right)\mathbf{1}\left(\Delta_2 y_{t+1} < 0\right)\\ &+\left(1-S_{t-1}\right)\mathbf{1}\left(\Delta y_{t+1} > 0\right)\mathbf{1}\left(\Delta_2 y_{t+2} > 0\right)\\ &-\left(1-S_{t-1}\right)\left(1-S_{t-2}\right)\mathbf{1}\left(\Delta y_{t+1} > 0\right)\mathbf{1}\left(\Delta_2 y_{t+2} > 0\right)\mathbf{1}\left(\Delta y_t > 0\right)\mathbf{1}\left(\Delta_2 y_{t+1} > 0\right) \end{aligned}$$

Hence, given that we were in an expansion in $t-1$ and $t-2$ i.e. $S_{t-1} = 1, S_{t-2} = 1$, these are in F_t and we have both

$$S_{t+1} = \left[1-\mathbf{1}\left(\Delta y_{t+1} \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+2} \leq 0\right)\right]\left[1-\mathbf{1}\left(\Delta y_t \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+1} \leq 0\right)\right]$$

and

$$\begin{aligned} \Pr(S_t &= 0|F_t) = E\{\mathbf{1}\left(\Delta y_{t+1} \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+2} \leq 0\right) + \mathbf{1}\left(\Delta y_t \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+1} \leq 0\right)\\ &\quad -\mathbf{1}\left(\Delta y_{t+1} \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+2} \leq 0\right)\mathbf{1}\left(\Delta y_t \leq 0\right)\mathbf{1}\left(\Delta_2 y_{t+1} \leq 0\right)|F_t)\\ &= h(F_t). \end{aligned}$$

Clearly $h(\cdot)$ will be different to $g(\cdot)$. Again this can be evaluated numerically. A similar expression can be found if only S_{t-2} is known.

4 Predicting Negative Growth: Can Non-linear Models of GDP Growth Help?

The previous section drew attention to studying $\Pr(\Delta y_{t+1} < 0|F_t)$ as a first test of the ability to predict a recession. So far little mention has been made of the relationship between current and past growth, but implicitly this has been taken to be linear. One might allow Δy_t to also depend upon the state of the economy at $t-j$, S_{t-j}, and this is often mentioned as a possibility. Of course, since S_{t-j} depends on growth rates in GDP, it is still the case that the relationship is between growth rates. But this ignores the fact that S_t is a parsimonious summary of these and that it also introduces some non-linear structure through the fact that S_t depends on the sign of the growth rate and not the magnitude. Fitting a Probit model to $1(\Delta y_{t+1} < 0)$ for the Euro Area, with explanatory variables Δy_{t-1} and S_{t-1}, suggests that the probabilities are much the same as if one had just used Δy_{t-1}. This is also true of the US if one uses the S_{t-1} determined by BBQ.[10]

An alternative modification is to allow for GDP growth to depend in a non-linear way on its past history. Many non-linear models for Δy_t have been proposed, and one often sees comments that these produce better forecasts of GDP growth than linear models. A popular one that is used in a lot in the business cycle literature is that of a Hidden Layer Markov Chain, introduced into econometrics by Hamilton (1979). This is often given the shortened descriptor of a Markov Switching (MS) model, with the simplest variant having the form

$$\begin{aligned} \Delta y_t &= \mu_t + \beta \Delta y_{t-1} + \sigma \varepsilon_t && (5) \\ \mu_t &= \mu_1 \xi_t + (1 - \xi_t) \mu_0 && (6) \\ p_{ij} &= \Pr(\xi_t = i | \xi_{t-1} = j), && (7) \end{aligned}$$

where ξ_t is a binary random variable that follows a first order Markov process with transition probabilities p_{ij} and ε_t is $n.i.d(0,1)$. More complicated models are available but we doubt that these improve the recession predictions - see for example the discussion in Engel et al (2005). Although the MS model in $(5)-(7)$ could be fitted to the Euro area it was clear that it was an inappropriate model since the sample mean of the $1(\Delta y_{t+1} < 0)$ produced by simulating it was .44 versus the .12 in the data. Hence it was producing far too many negative growth rates. If one just fitted a linear AR(1) and simulated it this probability was .11. So one would have to reject this MS model. It is a curious fact that almost no analysis is given of the fit of MS models.

[10] BBQ S_t has a timing difference to the NBER S_t in 1974/5 since the NBER recession starts in 1974/1 while BBQ has it at 1974/3. Of course the NBER dating was not available when predicting GDP growth in 1974/2.

This simple test might be a good way of determining whether they provide a satisfactory description of the data, particularly if they are to be used for "business cycle analysis". For the US one gets a much better description of the data with the MS model, although even here there is evidence that the model does not fit the data, since the sample mean of $1(\Delta y_{t+1} < 0)$ in the data is .18, but it was .11 using data simulated from the estimated model. In any event the MS model would predict that $E(1(\Delta y_{t+1} < 0) \, |\Delta y_t)$ would be around .13 when growth Δy_t was around zero i.e. it is still highly unlikely that one can predict a negative growth in activity with that non-linear model.

5 Predicting Negative Growth and Recessions: Using Multivariate Information to Model GDP Growth

So far we have looked at whether one can predict the sign of Δy_{t+1} with past growth and state information and found that this is not likely. The fact that we are looking for the shocks that cause movements in future growth suggests that more success might be had by concentrating on variables that contain some forward-looking information. The fact that this is a crucial search can be dramatized by looking at the recessions emerging out of a model with credit and an external finance premium by Gilchrist et al (2009). In their model the cycle is around 18 quarters long (this is for per capita GDP). But if the contemporaneous shocks are excluded from output growth, since they are items that are not predictable, then cycles would be around 38 quarters long on average i.e. the shocks reduce cycle length by almost 5 years, showing how crucial they are to outcomes, and why predicting the business cycle is really about predicting future shocks.

A variable often used in an attempt to improve predictive power is the spread between long and short interest rates and there is now a large literature suggesting that such a spread variable is good at doing so e.g. Estrella and Mishkin (1978). There are also models that use multi-variate information to make predictions. Thus Canova and Ciccarelli (2004) use a VAR which is estimated across a number of economies. One that has attracted substantial attention is the Qual-VAR model of Dueker (2005) in which a vector of variables including $S_t, \Delta y_t$ and interest rates are modelled as a latent variable VAR. This structure is then used to generate forecasts of S_{t+1}. In the following sub-sections we look at the utility of various spreads and leading indicators, as well as the Qual-VAR model, for predicting negative growth and recessions.

5.1 The Predictive Utility of Spreads

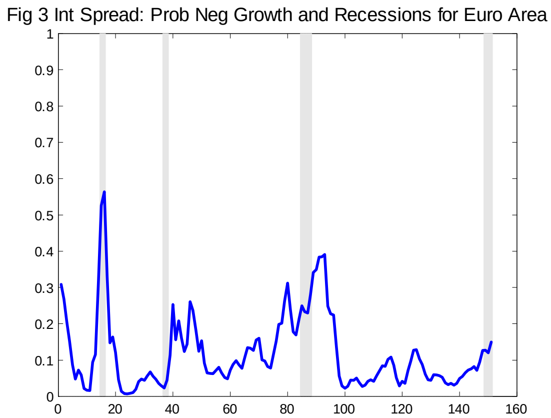
It has often been suggested that the spread between the ten year bond rate and the three month bill rate is informative for anticipating recessions. Indeed there are hundreds of articles looking at this for a variety of countries. Here we consider how useful it is for predicting negative growth one quarter ahead.

5.1.1 For Negative Growth in the Euro Area

Moneta (2005) suggested that the spread was a good predictor of Euro Area recessions, where he defined a recession as two periods of negative growth and lagged the spread four periods. Figure 3 shows the predictions from a Probit model of negative growth over the period 1971:1-2008:4 using spread data constructed for the Euro area by Anderson et al (2007). With the exception of the 1974/5 recession there seems little to be gained from using the spread as an indicator of a forthcoming recession. The most striking difference is in 1982 where Moneta's figure 1 (p276) records a probability of a recession above .8. What is peculiar about this is that he records a double dip recession in the Euro Area in the early 1980s, similar to US experience, but this does not appear in the standard recession dates for the Euro area. Moreover in the GDP figures we utilize there is no negative growth in the years 1982/3, so one would not record a recession using his two periods of negative growth rule.

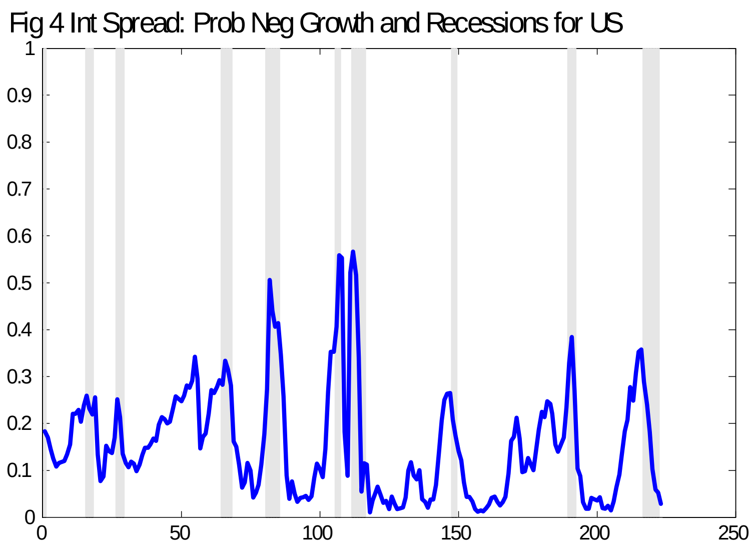
5.1.2 For Negative Growth in the US

In what follows we look at the US case as the predictive efficacy of spreads for that country's recessions has been a constant theme in the literature. As before, focussing on the first period the recession begins in, we get probabilities of negative growth for the nine recessions between 1954:2 and 2008:4 of .23, .21, .33, .51, .56, .52, .17, .38, and .24. The information used in this prediction was the spread lagged two periods (the best for predicting S_{t+1}



according to Estrella and Mishkin). The estimated Probit model shows a probability of negative growth of .31 when there is a zero spread, rising to .51 when the spread is -100 basis points. The latter is a very rare occurrence in US history. In fact, with the exception of 1973:3, the only other time the term structure inverted to such an extent was during the "Volcker experiment" over 1979-1982, when the Fed targeted money supply. In only the 1974/5 and double-dip recessions of the early 1980s would the spread have managed to indicate a negative growth rate. Figure 4 shows a plot of $\Pr(\Delta y_{t+1}|sp_{t-2})$ from 1953/2 until 2009/2.

If one looks at the pseudo-R^2 from the Probit model one finds it is .07 (with GDP growth), .16 (when the spread is added to growth as a regressor), .18 (with growth, spread and S_{t-2}), and .24 (with growth, spread and S_t). So spreads do contribute but not a great deal. We introduced S_t as suggested by Dueker (1997), and much applied research since then has used it e.g. Kauppi and Saikkonen (2008). Of course, as explained earlier, S_t is not available for prediction purposes, and to construct it one needs to know future growth outcomes. Because it is a function of future outcomes, it should not therefore be surprising that it will produce a much better fit to future data. In order to do a proper comparison it is not $S(t)$ that we should use but the expected value of $S(t)$ conditional upon whatever information is available at t, and we have discussed how to compute this earlier. If one does that there is only a marginal improvement. One recommendation therefore is that Probit models which include S_t as regressors can easily produce misleading accounts of the explanatory power of spreads, and so the inclusion of the variable in these



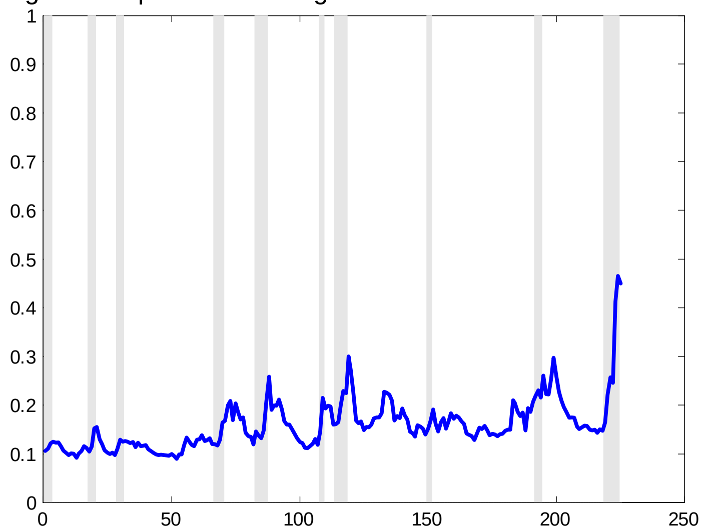
relations needs to be treated with caution. Because S_t would be known to be S_{t-2} if both Δy_t and Δy_{t-1} were positive (as the peak in y_t could not be at $t-2$ and $t-1$), using S_t as a regressor utilizes information that Δy_t and Δy_{t-1} have different signs.

Another spread that has been mentioned as a possible indicator is that of the spread between the yields on Baa bonds and the 10 year bond rate e.g. Gilchrist et al. (2009). As Figure 5 reveals, with the exception of the last recession, this spread does not have much predictive success.

5.2 The Predictive Utility of Some Euro Area Activity Indicators

We have seen papers that suggest there are Euro area indicators that might be used for predicting recessions. But the data used was not available to us. Camacho and Perez-Quiros (2010) is an exception. Their indicators begin at various times, but the earliest is in 1991, and the data available to us finished in 2007, so there was only one recession over the sample period. Some of the indicators were proprietary and so not deposited in the *Journal of Applied Econometrics* data base. Hard indicators related to various forms of GDP estimates for quarters before the one being forecast (flash, first and second

Fig 5 Baa Spread: Prob Neg Growth and Recessions for US



revisions) as well as forecasts and series on employment, sales and exports. Since we have already argued that exact knowledge of past GDP growth would add little to the predictive ability we ignore these. Soft indicators were composed of various survey type information. The series available to be used were BNB, ESI, IFO, EMP, EX and IPI (Table 1 of their paper give the acronyms).

Table 2 looks at the ability of the Euro-sting indicators to predict the only recession in the sample period. To get these predictions we fitted a Probit model to the binary variable recording negative growth and the series of the previous paragraph. The recession ran from 1992/2-1993/1, but we present some probabilities before and after the recession. In the Probit model the only significant coefficient was that of IFO (Germany IFO Business Climate Index).

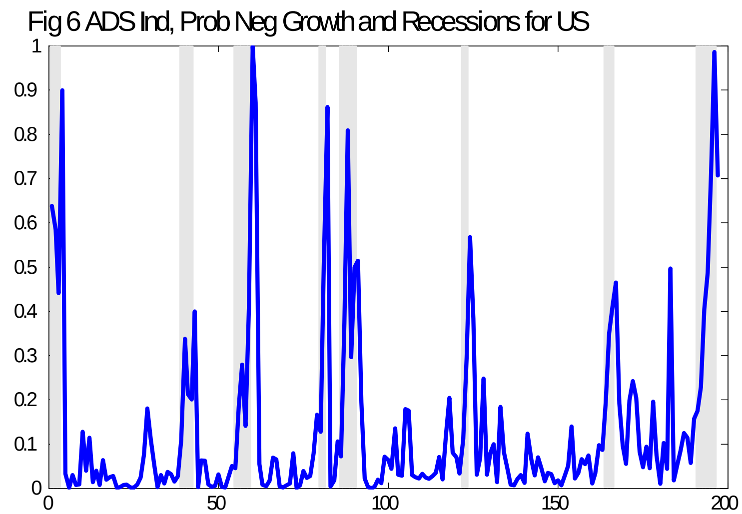
Table 2 : Probabilities of Predicting $\Delta y_{t+1} < 0$, Euro 1992/3 Recession			
		Neg Gwth	Prob
1991/3		Yes	.26
1991/4		No	.32
1992:1		No	.67
1992:2		Yes	.18
1992:3		Yes	.54
1992:4		Yes	.29
1993:1		Yes	.60
1993:2		No	.51
1993:3		No	.63
1993:4		No	.14

One can see from this that there are quite a few false alarms and the pattern we saw earlier regarding the inability to predict the first quarter of recessions is still present. It is possible that one can improve these results by some smoothing of the individual series, but one would really want to have a longer history of them so one can assess their utility based on their capacity to predict earlier recessions. Because the 2008 recession did not begin until the second quarter, none of the indicators in the data base related to that, and so we were not able to do what would be a useful check using a second observed recession. It should also be observed that in 2003:2 there was a negative quarter of growth, but the indicators only showed a probability of .11, slightly above the unconditional probability of .09 over the sample period.

5.3 The Predictive Utility of Some US Indicators

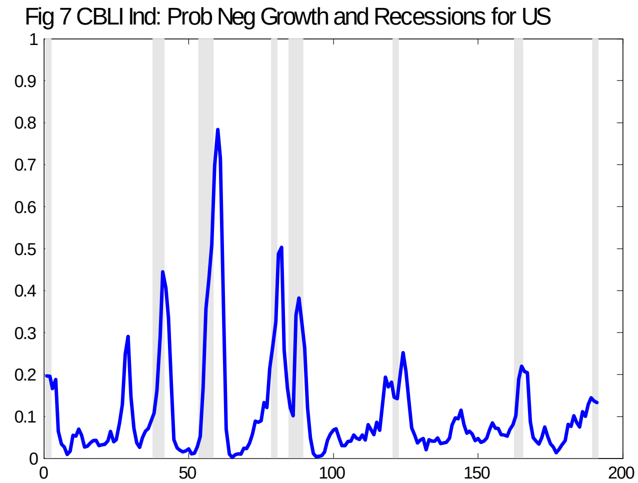
Two series that have been suggested as having the potential for predicting recessions are the Reserve Bank of Philadelphia index developed by Aruoba et al (2009) (ADS) and the Conference Board composite leading indicator series (CBLI). The latter has a long history, albeit with rather mixed success, but there has been a recent claim by Berge and Jorda (2010) that it is a good predictor and certainly superior to ADS.

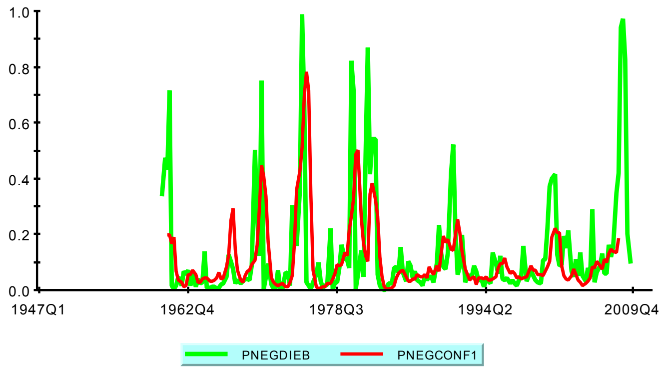
There are two ways one might look at the probability of negative growth with the ADS index. If $R_t = 1(\Delta y_t < 0)$ one might estimate the Probit



model $\Pr(R_t = 1|ADS_t) = \Phi(\alpha + \beta ADS_t)$, where ADS_t is the value of the index available just before the quarter. The other would be to estimate $\Pr(R_t = 1|ADS_t) = \Phi(\beta(ADS_t + .8))$, as it is often the case that the value of $-.8$ is regarded as a threshold value for whether one is likely to enter a recession or not. We will refer to these as Models I and II. The problem with using Model II is that the threshold of -.8 was probably chosen by noting that this was the threshold value such that all recessions in the period before 2008 would have been predicted perfectly. Because of that we would expect Model II to feature a high probability of predicting negative growth. The only real test of the model then would be the ability to predict the 2008 recession and here the first-period growth probability prediction was just .31. If one decided that the data should decide the threshold (Model I) then the probability of the 2008 recession would be .32. Of course Model I does produce lower probabilities in general since it has not been designed to produce high ones. It is what is contained in Figure 6. We should note that the Model II index produces some very high probabilities of negative growth away from recession times e.g. in 1989:3 it was .5, 1992:1 it was .42 and in 2003:2 it was .46. It is also the case that this index has an unconditional probability of a negative growth rate of .21 versus the .135 of the data, whereas the Model I index matches this.

Figure 7 presents the same graph but using the CBLI index. It is not





entirely clear how to use the index. Berge and Jorda originally indicate that it is the annual growth that is used but later say "we use this procedure to predict the probability of recession from 1960 to 2010 using contemporaneous LEI data". The latter suggests that it might be quarterly growth which is used. Since this has been a common transformation of the CBLI - see Filardo (1999) - we used it in Figure 7. Indeed, the prediction performance was better with this than with the annual growth measure. But it is clear that the results we get are nowhere near as impressive as they report. We also note that the ADS index is a better predictor than the CBLI, as seen in Fig 8. Here we fit a Logit rather than Probit as that seems to be what they suggest they do.

5.4 Qual VAR

Dueker(2005) described a Qual-VAR which has the (simplified) form

$$
\begin{aligned}
z_t &= \alpha_{yy} z_{t-1} + \alpha_{yz} \psi_{t-1} + \varepsilon_t && (8)\\
\psi_t &= \alpha_{zy} z_{t-1} + \alpha_{zz} \psi_{t-1} + \upsilon_t && (9)\\
\zeta_t &= 1(\psi_t > 0), \zeta_t = S_t && (10)
\end{aligned}
$$

where z_t is a vector of observable variables, ψ_t is a latent variable describing economic activity and the shocks $\varepsilon_t, \upsilon_t$ are normally and independently distributed with a zero expectation. z_t, ψ_t follow a VAR(1) in (8) and (9). Basically one can think of this as a model in which the "level of activity" is captured by a latent variable ψ_t. The NBER Dating Committee are assumed to express opinions about the variable ψ_t through their published decisions about whether the economy is in an expansion or a contraction (S_t), and that is described in (10). This model is then estimated using data on z_t *and* S_t. The values of S_t determine what distribution one should draw ψ_t from. Specifically, at time t, if we observe that $S_t = 1$, a draw is made from the truncated distribution $\psi_t|(\psi_t > 0)$. Because S_t have been formed by the NBER after recessions and expansions have occurred, S_t should be related either directly to z_t or variables that are correlated with it. Thus S_t is a forward-looking endogenous variable, but Dueker effectively treats it as if it was exogenous. To see this note that the implications of the model above are

$$
\begin{aligned}
E(\zeta_t | z_{t-1}, \psi_{t-1}) &= \Pr(\psi_t > 0 | z_{t-1}, \psi_{t-1})\\
&= \Phi(\alpha_{zy} z_{t-1} + \alpha_{zz} \psi_{t-1})
\end{aligned}
$$

so that, adopting a linear approximation for exposition,

$$E(\zeta_t | z_{t-1}, \psi_{t-1}) = a z_{t-1} + b \psi_{t-1},$$

produces an explanation of ζ_t of the form

$$\zeta_t = S_t = a z_{t-1} + b \psi_{t-1} + \eta_t,$$

where $\eta_t = \zeta_t - E(\zeta_t | z_{t-1}, \psi_{t-1})$. Inverting this equation gives $\psi_{t-1} = \frac{1}{b}(S_t - a z_{t-1} - \eta_t)$ so that the model for z_t becomes

$$z_t = c z_{t-1} + d S_t + \xi_t. \tag{11}$$

Consequently, even though S_t did not appear explicitly in the original VAR, it was implicitly there because of the presence of the latent variable ψ_{t-1}.

Now if $\alpha_{zy} = 0$ we know from Kedem (1980) that ζ_t will be an infinite dimensional Markov Chain whose parameters depend only upon α_{zz}, and so the combination of (11) and the stationary process for S_t will effectively be the system that is being estimated. Conditioning upon S_t raises the issue of whether S_t actually equals ζ_t. We know that there will be an estimate of ζ_t that can be generated from $\{z_{t-j}\}_{j=0}^{\infty}$, but whether that corresponds to the way that the NBER construct S_t from z_t is problematic. There is probably some specification for the ψ_t process that will lead to a dating rule using z_t that will agree with the NBER states but whether it is the one in the Qual-VAR is another matter. Consequently, this difficulty points to the need to check for specification errors in the latent variable part of the Qual-VAR. In any case it is clear that the fact that S_t is being treated as if it is exogenous, when it actually depends on future values of z_t, will lead to inconsistent estimation of d unless one recognizes that dependence.

A more direct solution to this issue which uses the nature of the S_t in (1), is to define y_t in that equation as the latent variable ψ_t. We then have the VAR system

$$\begin{aligned}
z_t &= \alpha_{yy} z_{t-1} + \alpha_{yz}\psi_{t-1} + \varepsilon_t && (12)\\
\psi_t &= \alpha_{zy} z_{t-1} + \alpha_{zz}\psi_{t-1} + \upsilon_t && (13)\\
S_{t+1} &= S_t S_{t-1}\left[1 - \mathbf{1}\left(\Delta\psi_{t+1} \le 0\right)\mathbf{1}\left(\Delta_2\psi_{t+1} + \Delta\psi_{t+2} \le 0\right)\right] + S_t\left(1 - S_{t-1}\right)\\
&\quad + \left(1 - S_t\right)\left(1 - S_{t-1}\right)\mathbf{1}\left(\Delta\psi_{t+1} > 0\right)\mathbf{1}\left(\Delta_2\psi_{t+1} > 0\right). && (14)
\end{aligned}$$

The VAR in (12)-(14) incorporates both a latent variable and some non-linear structure and has some similarities to DSGE models with forward looking expectations. Estimation can be done by simulation methods. The simplest estimation approach would be to use indirect estimation and various auxiliary models could be used.

Dueker (2005) reports an application of his Qual-VAR to predicting the recession of 2001. The task was to forecast 2000:4-2003:3. Dueker assumes that $S_t = 1$ in 2000:3. It is necessary to have a way of generating $E_t z_{t+j}$ over the forecast period. One possibility is to produce forecasts of z_t using an AR(5) in z_t. Another is to use the broader set of variables in Dueker's paper and take the forecasts of the spread to be from a VAR(5) in GDP growth, inflation, the spread and an interest rate. We use both below.

Table 3 shows the probability of a recession over the period 2000:4-2003:3 given that the information used is just the knowledge of S_t in 2000:1 and 2000:2 along with the yield spread up to and including 2000:3 (as well as the other variables in the case of the VAR).

Table 3: Probability of a Recession, 2000:4-2003:3		
	AR(5)	VAR(5)
2000:4	.24	.24
2001:1	.36	.36
2001:2	.42	.45
2001:3	.42	.49
2001:4	.40	.49
2002:1	.37	.47
2002:2	.34	.44
2002:3	.30	.40
2002:4	.27	.36
2003:1	.24	.32
2003:2	.22	.29
2003:3	.20	.26

Comparing these to the results in Dueker (Table 2, p 100) we see that the pattern is the same but the latter reports a maximum probability of .57, which is a very high probability given such a weak recession (indeed Dueker notes that the Qual-VAR forecast of GDP growth never becomes negative). We were not able to replicate his Table 2 probabilities with the program Dueker supplied to us, getting instead a maximum probability of .55 and a probability in 2003:3 of .32, but these seem reasonably consistent.

To understand why our estimates are smaller consider first the comparison between the AR and VAR. The VAR produces higher probabilities because it features three forecasts of the spread that are negative, with values of -38,-34 and -2 basis points, whereas the AR never has any negative forecast, although there is one quarter of a small positive value. Since Dueker utilizes a VAR in his work one would therefore expect a probability of at least .5. It should be said that the AR produces a much better forecast of the actual path of the spread than the VAR, as there are no negative spreads ex-post in the forecast period. So it is not clear whether one gets a large probability of a recession simply due to an incorrect forecast of the spread over the recession. It would seem important that one would provide information on exactly what causes the probability of a recession to rise, and should be able to do this with the multivariate model that is used, rather than just treating it as a black box.

The other source of difference is that in 2003:3 the probability of a recession from the Qual-VAR is .29 which is high compared to the unconditional probability of .17 in the data. This suggests that the model has a tendency to assign a high probability to a recession. If we extend the forecast period for the AR and VAR models to 25 periods, the probability of a recession would be given as .174 i.e. both models return to the unconditional mean of S_t as the forecast. In contrast, simulating out the Qual-VAR produces an unconditional forecast of the probability of a recession of .39.[11] One problem may be that in the simulations used to do the Bayesian forecasts involve unstable VARs and these were retained provided the maximum root was less than 1.02. In a sense this is a specification test since the forecast should return to the unconditional mean in a stationary context, and S_t will be a stationary random variable. Thus the Qual-VAR does not seem to have this property and directs attention to the possibility of specification errors in it based on treating S_t as exogenous that were mentioned earlier. The methodology of the Qual-VAR seems not to have been well documented so predictions from it are more like those from a judgement rather than something that can be re-produced.

6 Changing The Event Defining Recessions and Turning Points

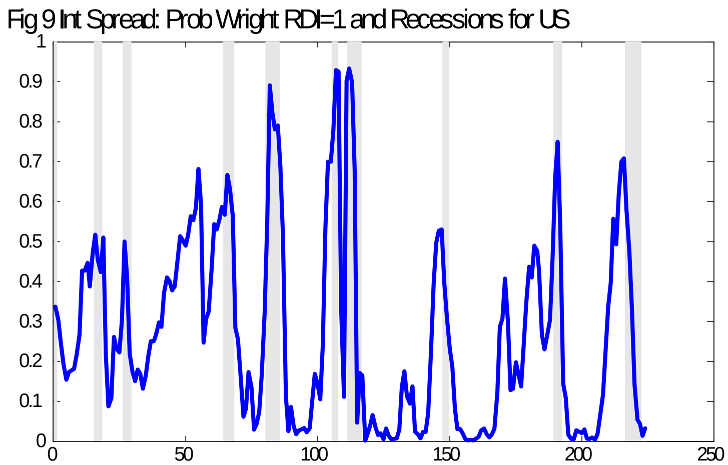
There are two ways that this can happen. In one approach a variety of series might be combined together to measure the level of economic activity. Many suggestions have been made e.g. the level of unemployment as well as industrial production. Indeed, the NBER S_t involve an analysis of the turning points of a number of series and this information is then combined in an unknown way by the NBER Dating Committee to produce the final

[11] In an econbrowser blog http://www.econbrowser.com/archives/2008/02/how_to_balance.html Deuker reports what seem to be probabilties of S_{t+1} being zero in the 2001 recession of around .42, which seems more in line with our finding. In his 12-period horizon forecast the probability of .17 is close to the unconditional forecast. There is no explanation of how the Qual VAR has been adjusted to produce such different results from that given in Deuker (2005). We also note that in the internet piece Dueker takes .35 to be the critical value that one compares the predicted probability to when deciding if a recession is being forecast, which again raises the issue of what is an appropriate threshold.

recession and expansion dates. Coincident indices generally combine together a number of series with fixed weights, while many factor models aiming to extract a common factor from a variety of series use a set of weights that may be varying. Obviously, it cannot be any easier to predict an indicator based on a variety of series than a single one, since one now has to forecast the sign of future growth in many series to find their turning points.

A different approach is to re-define the recession event. We will refer to these as a "recession-derivative indicator", RDI. A number of papers that suggest high probabilities of predicting a recession have used RDIs. One example that is often cited is Wright (1996). Wright has an RDI (RW_t) taking the value one if an NBER defined recession happens in the next four quarters and zero otherwise. To see how this affects outcomes take the following series for $S_t - \{1,1,1,1,1,0,0,0,1,1,1,1\}$ - which produces $R_t = 1 - S_t = \{0,0,0,0,0,1,1,1,0,0,0,0\}$. The binary numbers here correspond to when the NBER define expansions and recessions. The RDI used by Wright is then $RW_t = 1(\{R_{t+j} = 1\}_{j=1}^{4})$ and, for the S_t above, it will be $RW_t = \{0,1,1,1,1,1,1,0,?,?,?,?\}$, where ? indicates that a decision can't be made as not enough future information is available. It is clear from this that the mean of RW_t is different from that for R_t i.e. the unconditional probability that $R_t = 1$ is much lower than the probability that $RW_t = 1$ (for the U.S. it is .15 versus .28 over the period 1953:2-2008:4). If one then describes a high $\Pr(RW_t = 1|F_t)$ as "predicting a recession", it can look as if there is much greater predictive success, but it is an artifact of the re-definition of the event being predicted.

Note that the rise in probability comes because expansions are not treated symmetrically with recessions. Thus, for the seventh observation in the R_t sequence, the following four values for R_t are $\{1,0,0,0\}$, and RW_7 was taken to be unity because of the fact that $R_8 = 1$. But, given that the quadruple $\{R_8, R_9, R_{10}, R_{11}\} = \{1,0,0,0\}$ largely consists of expansion periods, it might seem more appropriate that $RW_7 = 0$. Except for the instances in which ties occur, wherein RW might be either one or zero e.g. with the quadruple $\{0,0,1,1\}$, treating expansions and contractions symmetrically would just mean that $RW_j = \{R_{j-4}\}$. In this instance the probabilities of $R_t = 1$ and the resulting (symmetric) RDI, $RW_t = 1$, would be the same. Another important effect of moving to RW_t is that there is a timing change. In the example above consider predicting whether $RW_7 = 1$. Because this is effectively the second period into a recession, comparing it with the R_t outcomes will make it look as if one has managed to predict the recession in advance,



but again it is an artifact of changing the event being predicted.

One can see these effects in a number of ways. First suppose we fit the same model to R_t. Then $\{\Pr(R_{t+1} = 1|sp_{t-2}), P(RW_{t+1} = 1|sp_{t-2})\}$ for the recessions between 1954 and 2009 would be

$$\{.22, .45\}, \{.21, .41\}, \{.33, .66\}, \{.49, .89\}, \{.54, .93\}$$
$$\{.50, .89\}, \{.17, .31\}, \{.37, .75\}, \{.24, .47\}.$$

So the move from explaining recessions to an RDI has essentially doubled the probabilities, as noted above. The switch in timing also mentioned can be seen in Figure 9.

Another RDI used by Fair (1993), Anderson and Vahid (2001), and Galvao (2006) is similar, except that it defines a recession starting at t if the five quarters starting at t have two successive periods of negative growth. One can see that the RDI formed this way will be $R_t^* = \{1, 1, 0, 0, 0, 0, 0, 1, ?.?, ?, ?\}$. Again the timing has been changed and the unconditional probability of the recession defined event will likely be higher than for that describing recessions, R_t.

Canova and Ciccarelli (2004) look at turning points but they define a peak and trough in the *growth rates* and so are looking at a *growth rate cycle*. Of course this means that one is interested in whether $\Delta^2 y_t$ etc are negative, not Δy_t. Thus predictability of a turning point in the series of growth rates would involve a "first period test" of $\Pr(\Delta y_{t+1} - \Delta y_t < 0|F_t)$. Suppose $F_t = \Delta y_t$. Now, if Δy_t had a unit root, then Δy_t would have no predictive power for the event $1(\Delta y_{t+1} - \Delta y_t < 0)$ but, if it was white noise, then there is quite a bit. For the US regressing $1(\Delta y_{t+1} - \Delta y_t < 0)$ against Δy_t gives an R^2 of .24.

7 Conclusion

In response to the widespread criticism that macro-economists failed to predict the global recession coming from the Global Financial Crisis, we look at whether recessions can be predicted. The paper starts with a formula describing the evolution of the binary states summarizing expansions and contraction periods and uses this to suggest that a useful way to proceed is to ask whether it is possible to predict negative growth in economic activity. Some simple linear and non-linear models are first used to do this. These suggest that it is very difficult to predict a recession and it is only after it is underway that the prediction probability will be high. Finally, as the formula for state evolution indicates, to forecast a turning point in economic activity one needs to predict future shocks, and we consider a range of indicators designed to do this for the Euro Area and the U.S. The paper concludes by examining a literature that forecasts what we term recession-derived indicators. This can often be done quite well but we argue that it has few implications for forecasting recessions.

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